ANNEX 7 Uncertainty – TO BE UPDATED

The annual U.S. Inventory presents the best effort to produce estimates for greenhouse gas source and sink categories in the United States. These estimates were generated according to the UNFCCC reporting guidelines, following the recommendations set forth in the *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC/UNEP/OECD/IEA 1997), the *IPCC Good Practice Guidance* (IPCC 2000), the Good Practice Guidance for Land Use, Land-Use Change and Forestry (IPCC 2003), and the *2006 Guidelines for National Greenhouse Gas Inventories* (IPCC 2006). This Annex provides an overview of the uncertainty analysis conducted to support the U.S. Inventory, describes the sources of uncertainty characterized throughout the Inventory associated with various source categories (including emissions and sinks), and describes the methods through which uncertainty information was collected, quantified, and presented.

7.1. Overview

Some of the current inventory estimates, such as those for CO_2 Emissions from Fossil Fuel Combustion for example, have a relatively low level of uncertainty associated with them. Other categories of emissions exist, however, for which the inventory emission estimates are considered less certain. The major types of uncertainty associated with these inventory estimates are (1) model uncertainty, which arises when the emission and/or removal estimation models used in developing the inventory estimates do not fully and accurately characterize the respective emission and/or removal processes (due to a lack of technical details or other resources), resulting in the use of incorrect or incomplete estimation methodologies and (2) parameter uncertainty, which arises due to a lack of precise input data such as emission factors and activity data.

The model uncertainty can be analyzed by comparing model results with those of other models developed to characterize the same emission (or removal) process. However, it would be very difficult—if not impossible—to quantify the model uncertainty associated with the inventory estimates (primarily because, in most cases, only a single model has been developed to estimate emissions from any one source). Therefore, model uncertainty was not quantified in this report. Nonetheless, it has been discussed qualitatively, where appropriate, along with the individual source category description and inventory estimation methodology.

Parameter uncertainty is, therefore, the principal type and source of uncertainty associated with the national inventory estimates and is the main focus of the quantitative uncertainty analyses in this report. Parameter uncertainty has been quantified for all of the emission sources and sinks in the U.S. Inventory, with the exception of two source categories, whose emissions are not included in the Inventory totals.

The primary purpose of the uncertainty analysis conducted in support of the U.S. Inventory is (i) to determine the quantitative uncertainty associated with the emission (and removal) estimates presented in the main body of this report [based on the uncertainty associated with the input parameters used in the emission (and removal) estimation methodologies] and (ii) to evaluate the relative importance of the input parameters in contributing to uncertainty in the associated source category inventory estimate and in the overall inventory estimate. Thus, the U.S. Inventory uncertainty analysis provides a strong foundation for developing future improvements and revisions to the Inventory estimation process. For each source category, the analysis highlights opportunities for changes to data measurement, data collection, and calculation methodologies. These are presented in the "Planned Improvements" sections of each source category's discussion in the main body of the report.

7.2. Methodology and Results

The United States has developed a QA/QC and uncertainty management plan in accordance with the IPCC *Good Practice Guidance*. Like the quality assurance/quality control plan, the uncertainty management plan is part of a continually evolving process. The uncertainty management plan provides for a quantitative assessment of the inventory analysis itself, thereby contributing to continuing efforts to understand both what causes uncertainty and how to improve inventory quality (EPA 2002). Although the plan provides both general and specific guidelines for implementing quantitative uncertainty analysis, its components are intended to evolve over time, consistent with the inventory estimation process. The U.S. plan includes procedures and guidelines, and forms and templates, for developing quantitative assessments of uncertainty in the national Inventory estimates.

The IPCC *Good Practice Guidance* recommends two approaches—Tier 1 and Tier 2—for developing quantitative estimates of uncertainty in the inventory estimate of individual source categories and the overall inventory. Of these, the Tier 2 approach is both more flexible and more powerful than Tier 1; both methods are described in the next section. The United States is currently in the process of implementing a multi-year strategy to develop quantitative estimates of uncertainty for all source categories using the Tier 2 approach. This year, a Tier 2 approach was implemented for all source categories except HCFC-22 production and Composting.

The current Inventory reflects significant improvements over the previous publication in the extent to which the Tier 2 approach to uncertainty analysis was adopted. Each of the new Tier 2 analyses reflect additional detail and characterization of input parameters using statistical data collection, expert elicitation methods and more informed judgment. Emissions and sinks from International Bunker Fuels, Biomass Combustion, and Indirect Greenhouse Gas Emissions are not included in total emissions estimated for the U.S. Inventory; therefore, no quantitative uncertainty estimates have been developed for these source categories.

Tier 1 and Tier 2 Approach

The Tier 1 method for estimating uncertainty is based on the error propagation equation. This equation combines the uncertainty associated with the activity data and the uncertainty associated with the emission (or the other) factors. The Tier 1 approach is applicable where emissions (or removals) are usually estimated as the product of an activity value and an emission factor or as the sum of individual sub-source category values. Inherent in employing the Tier 1 method are the assumptions that, for each source category, (i) both the activity data and the emission factor values are approximately normally distributed, (ii) the coefficient of variation associated with each input variable is less than 30 percent, and (iii) the input variables (i.e., values to be combined) are not correlated.

The Tier 2 method is preferred (i) if the uncertainty associated with the input variables are significantly large, (ii) if the distributions underlying the input variables are not normal, (iii) if the estimates of uncertainty associated with the input variables are significantly correlated, and/or (iv) if a sophisticated estimation methodology and/or several input variables are used to characterize the emission (or removal) process correctly. In practice, the Tier 2 is the preferred method of uncertainty analysis for all source categories where sufficient and reliable data are available to characterize the uncertainty of the input variables.

The Tier 2 method employs the Monte Carlo Stochastic Simulation technique (also referred to as the Monte Carlo method). Under this method, estimates of emissions (or removals) for a particular source category are generated many times (equal to the number of iterations specified) using an uncertainty model--which is an emission (or removal) estimation equation that simulates or is the same as the inventory estimation model for a particular source category. These estimates are generated using the respective, randomly-selected values for the constituent input variables using a simulation-software such as @RISK or Crystal Ball.

Characterization of Uncertainty in Input Variables

Both Tier 1 and Tier 2 uncertainty analyses require that all the input variables are well-characterized in terms of their Probability Distribution Functions (PDFs). In the absence of particularly convincing data measurements, sufficient data samples, or expert judgments that determined otherwise, the PDFs incorporated in the current source category uncertainty analyses were limited to uniform, triangular, lognormal, or normal. The choice among these four PDFs depended largely on the observed or measured data and expert judgment.

Source Category Inventory Uncertainty Estimates

Discussion surrounding the input parameters and sources of uncertainty for each source category appears in the body of this report. Table A-243 summarizes results based on assessments of source category-level uncertainty. The table presents base year (1990 or 1995) and current year (2006) emissions for each source category. The combined uncertainty (at the 95 percent confidence interval) for each source category is expressed as the percentage deviation above and below the total 2006 emissions estimated for that source category. Source category trend uncertainty is described below.

Table A-243: Summary Results of Source Category Uncertainty Analyses

Source Category	Base Year Emissions*	2006 Emissions	2006 Uncertainty	
	Tg CO_2 Eq.	Tg CO_2 Eq.	Low	High
CO_2	**5,067.2**	**5,983.1**	**-2%**	**5%**
Fossil Fuel Combustion	4,724.1	5,639.4	-2%	5%
Non-Energy Use of Fuels	117.2	138.0	-20%	9%
Natural Gas Systems	33.7	28.5	-23%	45%
Cement Manufacture	33.3	45.7	-13%	14%
Lime Manufacture	12.0	15.8	-8%	8%
Limestone and Dolomite Use	5.5	8.6	-7%	7%
Soda Ash Manufacture and Consumption	4.1	4.2	-7%	7%
Carbon Dioxide Consumption	1.4	1.6	-21%	26%
Municipal Solid Waste Combustion	10.9	20.9	-20%	13%
Titanium Dioxide Production	1.2	1.9	-12%	13%
Aluminum Production	6.8	3.9	-5%	5%
Iron and Steel Production	84.9	47.7	-17%	17%
Ferroalloy Production	2.2	1.5	-12%	12%
Ammonia Manufacture and Urea Consumption	16.9	12.4	-10%	12%
Phosphoric Acid Production	1.5	1.2	-18%	19%
Petrochemical Production	2.2	2.6	-35%	39%
Silicon Carbide Production and Consumption	0.4	0.2	-10%	10%
Lead Production	0.3	0.3	-16%	16%
Zinc Production	0.9	0.5	-21%	25%
Cropland Remaining Cropland	7.1	8.0	0%	0%
Petroleum Systems	0.4	0.3	-28%	144%
Land Use, Land-Use Change, and Forestry	*(736.6)*	*(882.9)*	0%	0%
International Bunker Fuelsb	*113.7*	*125.7*		
Wood Biomass and Ethanol Consumption[b]	*219.3*	*234.7*		
CH_4	**608.7**	**542.3**	**0%**	**0%**
Stationary Combustion	7.4	6.2	-31%	116%
Mobile Combustion	4.7	2.4	-16%	18%
Coal Mining	84.1	58.5	-9%	30%
Abandoned Underground Coal Mines	6.0	5.4	-17%	19%
Natural Gas Systems	124.7	102.4	-23%	45%
Petroleum Systems	33.9	28.4	-28%	144%
Petrochemical Production	0.9	1.0	-9%	9%
Silicon Carbide Production and Consumption	0.0	0.0	-9%	10%
Iron and Steel Production	1.3	0.9	-8%	8%
Ferroalloy Production	0.0	0.0	-12%	12%
Enteric Fermentation	126.9	126.2	-11%	18%
Manure Management	31.0	41.4	-18%	20%
Rice Cultivation	7.1	5.9	-15%	16%
Field Burning of Agricultural Residues	0.7	0.8	-65%	79%
Forest Land Remaining Forest Land	7.1	11.6	0%	0%
Landfills	149.6	125.7	-41%	34%
Wastewater Treatment	23.0	23.9	-37%	48%
Composting	0.3	1.6	-50%	50%
International Bunker Fuels[b]	*0.2*	*0.2*		
N_2O	**544.9**	**531.7**	**0%**	**0%**
Stationary Combustion	12.8	14.5	-24%	190%
Mobile Combustion	43.5	33.1	-19%	19%
Adipic Acid Production	15.3	5.9	-15%	16%
Nitric Acid Production	17.0	15.6	-40%	41%
Manure Management	12.1	14.3	-16%	24%
Agricultural Soil Management	430.6	429.7	0%	0%
Field Burning of Agricultural Residues	0.4	0.5	-64%	73%
Wastewater Treatment	6.3	8.1	-78%	100%

N2O from Product Uses	4.4	4.4	-2%	2%
Municipal Solid Waste Combustion	0.5	0.4	-66%	184%
Composting	0.4	1.8	-50%	50%
Settlements Remaining Settlements	1.0	1.8	-79%	280%
Forest Land Remaining Forest Land	0.8	1.5	0%	0%
International Bunker Fuels[b]	*1.0*	*1.1*		
HFCs, PFCs, and SF_6	**88.9**	**144.7**	**0%**	**0%**
Substitution of Ozone Depleting Substances	0.3	107.3	-9%	20%
Aluminum Production	18.5	2.5	-8%	8%
HCFC-22 Production	35.0	13.8	-10%	10%
Semiconductor Manufacture	2.9	4.8	-10%	8%
Electrical Transmission and Distribution	26.7	13.2	-16%	17%
Magnesium Production and Processing	5.4	3.2	-14%	14%
Total	**6,309.7**	**7,201.9**	**-1%**	**5%**
Net Emission (Sources and Sinks)	**5,573.1**	**6,318.9**	**-3%**	**7%**

Notes:
Totals may not sum due to independent rounding.
*Base Year is 1990 for all sources except Substitution of Ozone Depleting Substances, for which the United States has chosen to use 1995.
+ Does not exceed 0.05 Tg CO_2 Eq.
[a] Sinks are only included in net emissions total.
[b] Emissions from International Bunker Fuels and Biomass Combustion are not included in totals.

Overall (Aggregate) Inventory Uncertainty Estimate

The overall uncertainty estimate for the U.S. greenhouse gas emissions inventory was developed using the IPCC Tier 2 uncertainty estimation methodology. The uncertainty models of all the emission source categories could not be directly integrated to estimate the overall uncertainty estimates due to software constraints in integrating multiple, large uncertainty models. Therefore, an alternative approach was adopted to develop the overall uncertainty estimates. The Monte Carlo simulation output data for each emission source category uncertainty analysis were combined and the probability distribution was fitted to the combined simulation output data, where such simulated output data were available. If such detailed output data were not available for particular emissions sources, individual probability distributions were assigned to those source category emission estimates based on the most detailed data available from the quantitative uncertainty analysis performed.

For the HCFC-22 production and for parts of Agricultural Soil Management source categories, Tier 1 uncertainty results were used in the overall uncertainty analysis estimation. However, for all other emission sources (excluding international bunker fuels, CO_2 from biomass combustion), Tier 2 uncertainty results were used in the overall uncertainty estimation.

The results from the overall uncertainty model results indicate that the 2005 U.S. greenhouse gas emissions are estimated to be within the range of approximately 7,200 to 7,600 Tg CO_2 Eq., reflecting a relative 95 percent confidence interval uncertainty range of -1 percent to 5 percent with respect to the total U.S. greenhouse gas emission estimate of approximately 7,260 Tg CO_2 Eq. The uncertainty interval associated with total CO_2 emissions, which constitute about 84 percent of the total U.S. greenhouse gas emissions in 2005, ranges from -2 percent to 5 percent of total CO_2 emissions estimated. The results indicate that the uncertainty associated with the inventory estimate of the total N_2O emissions is the largest (-16 percent to 24 percent), followed by the total inventory CH_4 emission estimate (-10 percent to 16 percent), and high GWP gas emissions (-6 percent to 16 percent).

A summary of the overall quantitative uncertainty estimates are shown below, in Table A-244.

Table A-244. Quantitative Uncertainty Assessment of Overall National Inventory Emissions (Tg CO_2 Eq. and Percent)

Gas	2005 Emission Estimate (Tg CO_2 Eq.)	Uncertainty Range Relative to Emission Estimate[a] (Tg CO_2 Eq.)		Uncertainty Range Relative to Emission Estimate[a] (%)		Mean[b] (Tg CO_2 Eq.)	Standard Deviation (Tg CO_2 Eq.)
		Lower Bound[c]	Upper Bound[c]	Lower Bound[c]	Upper Bound[c]		
CO_2	6,089.5	5,992.1	6,397.2	-2%	5%	6,193.5	106.0
CH_4	539.3	487.5	623.6	-10%	16%	554.0	34.6
N_2O	468.6	392.7	578.8	-16%	24%	486.0	47.5
PFC, HFC & SF_6[d]	163.0	152.8	188.6	-6%	16%	170.2	9.3
Total	**7,260.4**	**7,170.3**	**7,635.0**	**-1%**	**5%**	**7,403.7**	**120.9**

Net Emissions (Sources and Sinks)	**6,431.9**	**6,256.1**	**6,862.4**	**-3%**	**7%**	**6,559.9**	**155.5**

Notes:
[a] The emission estimates correspond to a 95 percent confidence interval.
[b] Mean value indicates the arithmetic average of the simulated emission estimates;
Standard deviation indicates the extent of deviation of the simulated values from the mean.
[c] The low and high estimates for total emissions were separately calculated through simulations and, hence, the low and high emission estimates for the sub-source categories do not sum to total emissions.
[d] The overall uncertainty estimate did not take into account the uncertainty in the GWP values for CH_4, N_2O and high GWP gases used in the inventory emission calculations for 2005.

Trend Uncertainty

In addition to estimates of uncertainty associated with the current year's emission estimates, this Annex also presents estimates of trend uncertainty. The *IPCC Good Practice Guidance* defines trend as the difference in emissions between the base year (i.e., 1990) and the current year (i.e., 2006) inventory estimates. However, for purposes of understanding the concept of trend uncertainty, the emission trend is defined in this report as the percentage change in the emissions (or removal) estimated for the current year, relative to the emission (or removal) estimated for the base year. The uncertainty associated with this emission trend is referred to as trend uncertainty.

Under the Tier 1 approach, the trend uncertainty for a source category is estimated using the sensitivity of the calculated difference between base year and 2006 emissions to an incremental (i.e., 1 percent) increase in one or both of these values for that source category. The two sensitivities are expressed as percentages: Type A sensitivity highlights the effect on the difference between the base and the current year emissions caused by a 1 percent change in both, while Type B sensitivity highlights the effect caused by a change to only the current year's emissions. Both sensitivities are simplifications introduced in order to analyze correlation between base and current year estimates. Once calculated, the two sensitivities are combined using the error propagation equation to estimate overall trend uncertainty.

Under the Tier 2 approach, the trend uncertainty is estimated using Monte Carlo Stochastic Simulation technique. The trend uncertainty analysis takes into account the fact that base and the current year estimates often share input variables. For purposes of the current Inventory, a simple approach has been adopted, under which the base year source category emissions (or removals) are assumed to exhibit the same uncertainty characteristics as the current year emissions (or removals). Source category-specific PDFs for base year estimates were developed using 2005 uncertainty output data. These were adjusted to account for differences in magnitude between the two years' inventory estimates. Then, for each source category, a trend uncertainty estimate was developed using the Monte Carlo method. The overall inventory trend uncertainty estimate was developed by combining all source category-specific trend uncertainty estimates. These preliminary trend uncertainty estimates present the range of likely change from base year to 2005, and are shown in Table A- 245.

Table A- 245. Quantitative Assessment of Trend Uncertainty (Tg CO_2 Eq. and Percent)

Gas/Source	Base Year* (Tg CO_2 Eq.)	2005	Emissions Trend (%)	Trend Range[a] (%) Lower Bound	Upper Bound
CO_2	**5,061.6**	**6,089.5**	**20%**	**15%**	**26%**
Fossil Fuel Combustion	4,724.1	5,751.2	22%	16%	28%
Non-Energy Uses of Fossil Fuels	117.3	142.4	21%	-2%	52%
Natural Gas Systems	33.7	28.2	-16%	-44%	25%
Cement Manufacture	33.3	45.9	38%	14%	66%
Lime Manufacture	11.3	13.7	22%	8%	36%
Limestone and Dolomite Use	5.5	7.4	34%	22%	46%
Soda Ash Manufacture and Consumption	4.1	4.2	2%	-8%	14%
Carbon Dioxide Consumption	1.4	1.3	-6%	-28%	21%
Waste Combustion	10.9	20.9	92%	37%	171%
Titanium Dioxide Production	1.3	1.9	47%	16%	85%
Aluminum Production	6.8	4.2	-38%	-42%	-34%
Iron and Steel Production	84.9	45.2	-47%	-58%	-32%
Ferroalloy Production	2.2	1.4	-35%	-46%	-22%
Ammonia Production and Urea Application	19.3	16.3	-15%	-24%	-5%
Phosphoric Acid Production	1.5	1.4	-10%	-31%	18%

Petrochemical Production	2.2	2.9	30%	-25%	125%
Silicon Carbide Production and Consumption	0.4	0.2	-42%	-49%	-32%
Lead Production	0.3	0.3	-7%	-27%	17%
Zinc Production	0.9	0.5	-54%	-67%	-36%
Land-Use Change and Forestry (Sink)[a]	*(712.8)*	*(828.5)*	-7%	-33%	29%
International Bunker Fuels[b]	*113.7*	*97.2*	0%		
Wood Biomass and Ethanol Combustion[b]	*219.3*	*206.5*	0%		
CH_4	**609.1**	**539.3**	**-11%**	**-25%**	**6%**
Stationary Combustion	8.0	6.9	-13%	-64%	106%
Mobile Combustion	4.7	2.6	-45%	-50%	-40%
Coal Mining	81.9	52.4	-36%	-43%	-28%
Abandoned Coal Mines	6.0	5.5	-8%	-28%	17%
Natural Gas Systems	124.5	111.1	-11%	-40%	34%
Petroleum Systems	34.4	28.5	-17%	-64%	90%
Petrochemical Production	0.9	1.1	25%	11%	41%
Silicon Carbide Production and Consumption	+	+	-67%	-71%	-62%
Iron and Steel Production	1.3	1.0	-28%	-36%	-19%
Ferroalloy Production	+	+	-43%	-52%	-32%
Enteric Fermentation	115.7	112.1	-3%	-21%	20%
Manure Management	30.9	41.3	34%	2%	75%
Rice Cultivation	7.1	6.9	-3%	-81%	372%
Field Burning of Agricultural Residues	0.7	0.9	24%	4%	49%
Forest Land Remaining Forest Land	7.1	11.6	64%	-58%	519%
Landfills	161.0	132.0	-18%	-53%	43%
Wastewater Treatment	24.8	25.4	3%	-38%	71%
International Bunker Fuels[b]	*0.2*	*0.1*	-36%		
N_2O	**482.0**	**468.6**	**12%**	**-15%**	**47%**
Stationary Combustion	12.3	13.8	12%	-61%	230%
Mobile Combustion	43.7	38.0	-13%	-33%	14%
Adipic Acid Production	15.2	6.0	-61%	-81%	-19%
Nitric Acid Production	17.8	15.7	-12%	-31%	12%
Manure Management	8.6	9.5	10%	-16%	45%
Agricultural Soil Management	366.9	365.1	21%	-16%	73%
Field Burning of Agricultural Residues	0.4	0.5	36%	16%	60%
Wastewater Treatment	6.4	8.0	26%	-57%	281%
N_2O Product Usage	4.3	4.3	0%	-6%	5%
Municipal Solid Waste Combustion	0.5	0.4	12%	-79%	502%
Settlements Remaining Settlements	5.1	5.8	13%	-66%	272%
Forest Land Remaining Forest Land	0.8	1.5	98%	-24%	410%
International Bunker Fuels[b]	*1.0*	*0.9*	-10%		
HFCs, PFCs, and SF_6	**89.3**	**163.0**	**83%**	**66%**	**112%**
Substitution of Ozone Depleting Substances	0.3	123.3	36899%	30356%	45120%
Aluminum Production	18.5	3.0	-84%	-86%	-82%
HCFC-22 Production	35.0	16.5	-53%	-59%	-46%
Semiconductor Manufacture	2.9	4.3	48%	10%	98%
Electrical Transmission and Distribution	27.1	13.2	-51%	-60%	-41%
Magnesium Production and Processing	5.4	2.7	-51%	-54%	-48%
Total	**6,242.0**	**7,260.4**	**18%**	**12%**	**23%**
Net Emission (Sources and Sinks)	**5,529.2**	**6,431.9**	**22%**	**13%**	**31%**

Notes:
Totals may not sum due to independent rounding.
*Base Year is 1990 for all sources except Substitution of Ozone Depleting Substances, for which the United States has chosen to use 1995.
+ Does not exceed 0.05 Tg CO_2 Eq.
[a] Trend Range represents the 95% confidence interval for the change in emissions from Base Year to 2005.
[b] Sinks are only included in net emissions total.
[c] Emissions from International Bunker Fuels and Biomass Combustion are not included in totals.

7.3. Planned Improvements

Identifying the sources of uncertainties in the emission and sink estimates of the Inventory and quantifying the magnitude of the associated uncertainty is the crucial first step towards improving those estimates. Quantitative assessment of the parameter uncertainty may also provide information about the relative importance of input parameters (such as activity data and emission factors), based on their relative contribution to the uncertainty within the source category estimates. Such information can be used to prioritize resources with a goal of reducing uncertainties over time within or among inventory source categories and their input parameters. In the current Inventory, potential sources of model uncertainty have been identified for some emission sources, and preliminary uncertainty estimates based on their parameters' uncertainty have been developed for all the emission source categories, with the exception of international bunker fuels and wood biomass and ethanol combustion source categories, which are not included in the inventory totals.

Specific areas that require further research include:

- *Incorporating excluded emission sources.* Quantitative estimates for some of the sources and sinks of greenhouse gas emissions, such as from some land-use activities and industrial processes, could not be developed at this time either because data are incomplete or because methodologies do not exist for estimating emissions from these source categories. See Annex 5 of this report for a discussion of the sources of greenhouse gas emissions and sinks excluded from this report. In the future, efforts will focus on estimating emissions from excluded emission sources and developing uncertainty estimates for all source categories for which emissions are estimated.

- *Improving the accuracy of emission factors.* Further research is needed in some cases to improve the accuracy of emission factors used to calculate emissions from a variety of sources. For example, the accuracy of current emission factors applied to CH_4 and N_2O emissions from stationary and mobile combustion are highly uncertain.

- *Collecting detailed activity data.* Although methodologies exist for estimating emissions for some sources, problems arise in obtaining activity data at a level of detail in which aggregate emission factors can be applied. For example, the ability to estimate emissions of SF_6 from electrical transmission and distribution is limited due to a lack of activity data regarding national SF_6 consumption or average equipment leak rates.

In improving the quality of uncertainty estimates the following include areas that deserve further attention:

- *Refine Source Category and Overall Uncertainty Estimates.* For many individual source categories, further research is needed to more accurately characterize PDFs that surround emissions modeling input variables. In some cases, this might involve using measured or published statistics rather than relying on expert judgment if such data is available.

- *Include GWP uncertainty in the estimation of Overall level and trend uncertainty.* The current year's Inventory does not include the uncertainty associated with the GWP values in the estimation of the overall uncertainty for the Inventory. Including this source would contribute to a better characterization of overall uncertainty and help assess the level of attention that this source of uncertainty warrants in the future.

- *Improve characterization of trend uncertainty associated with base year Inventory estimates.* The characterization of base year uncertainty estimates could be improved. This would then improve the analysis of trend uncertainty, replacing the simplifying assumptions described in the "Trend Uncertainty" section above.

7.4. Additional Information on Uncertainty Analyses by Source

The quantitative uncertainty estimates associated with each emission and sink source category are reported in each chapter of this Inventory following the discussions of inventory estimates and their estimation methodology. This section provides additional descriptions of the uncertainty analyses performed for some of the sources, including the models and methods used to calculate the emission estimates and the potential sources of uncertainty surrounding them. These sources are organized below in the same order as the sources in each chapter of the main section of this Inventory. To avoid repetition, the following uncertainty analysis discussions of individual source categories do not include descriptions of these source categories. Hence, to better understand the details provided below, refer to the respective chapters and sections in the main section of this Inventory, as needed. All uncertainty estimates are reported relative to the 2006 Inventory estimates for the 95 percent confidence interval, unless otherwise specified.

Energy

The uncertainty analysis descriptions in this section correspond to some source categories included in the Energy Chapter of the Inventory.

Mobile Combustion (excluding CO_2)

Mobile combustion emissions of CH_4 and N_2O per vehicle mile traveled vary significantly due to fuel type and composition, technology type, operating speeds and conditions, type of emission control equipment, equipment age, and operating and maintenance practices.

Mobile combustion emissions of CH_4 and N_2O per vehicle mile traveled vary significantly due to fuel type and composition, technology type, operating speeds and conditions, type of emission control equipment, equipment age, and operating and maintenance practices. For more information on mobile combustion emission estimates, please refer to Mobile Combustion (excluding CO_2) section of the Energy chapter. The primary activity data, VMT, are collected and analyzed each year by government agencies. To determine the uncertainty associated with the activity data used in the calculations of CH_4 and N_2O emissions, the agencies and the experts that supply the data were contacted. Because few of these sources were able to provide quantitative estimates of uncertainty, expert judgment was used to assess the quantitative uncertainty associated with the activity data.

The estimates of VMT for highway vehicles by vehicle type in the United States were provided by FHWA (1996 through 2007), and were generated though the cooperation of FHWA and state and local governments. These estimates are subject to several possible sources of error, such as unregistered vehicles, and measurement and estimation errors. These VMT were apportioned by fuel type, based on data from DOE (1993 through 2007), and then allocated to individual model years using temporal profiles of both the vehicle fleet by age and vehicle usage by model year in the United States provided by EPA (2007c) and EPA (2000). While the uncertainty associated with the total national VMT is believed to be low, the uncertainty within individual source categories was considered to be higher due to the uncertainty associated with apportioning total VMT into individual vehicle categories, by fuel type, technology type, and by equipment age. The uncertainty in the individual estimates was assumed to be inversely related to the magnitude of estimated VMT (i.e., it was assumed that smaller sources had greater percentage uncertainty and vice-versa). Another source of uncertainty in the estimates occurs due to differences in FHWA and EPA data sources. For example, FHWA data are used for defining vehicle types and for developing the estimates of VMT by vehicle type, the estimates of VMT by fuel types are calculated using EPA's definition of vehicle categories (which differ from those of the FHWA).

A total of 171 highway data input variables were simulated through Monte Carlo Simulation technique using @RISK software. Variables included VMT and emission factors for individual conventional and alternative fuel vehicle categories and technologies. In developing the uncertainty estimation model, a normal distribution was assumed for all activity-related input variables (e.g., VMT) except in the case of buses, in which a triangular distribution was used. The dependencies and other correlations among the activity data were incorporated into the model to ensure consistency in the model specification and simulation. Emission factors were assigned uniform distributions, with upper and lower bounds assigned to input variables based on 95 percent confidence intervals of laboratory test data. In cases where data did not yield statistically significant results within the 95 percent confidence interval, estimates of upper and lower bounds were determined using expert judgments. For biodiesel vehicles, because no test data were available, consistent with the assumptions underlying the ANL GREET model, their N_2O and CH_4 emissions were assumed to be same as those for diesel vehicles of similar types. For other alternative fuel vehicles (AFVs), uncertainty estimates were developed based on conventional fuel vehicle emission factors and applicable multipliers, as described in the ICF's AFV emission factors memorandum to EPA (ICF 2006a). The results of the quantitative uncertainty analysis are reported as *quantitative uncertainty estimates* following the mobile source category emissions description in the Energy Chapter of this Inventory.

Emissions from non-highway vehicles account for 24 percent of CH_4 emissions from mobile sources and 11 percent of N_2O emissions from mobile sources in 2006. A quantitative analysis of uncertainty in the inventory estimates of emissions from non-highway vehicles has not been performed. However, sources of uncertainty for non-highway vehicles are being investigated by examining the underlying uncertainty of emission factors and fuel consumption data, and in the future, EPA will consider conducting a quantitative analysis of uncertainty for these sources.

Estimates of fuel consumption for off-highway vehicles (i.e., equipment used for agriculture, construction, lawn and garden, railroad, airport ground support, etc., as well as recreational vehicles) were generated by the EPA's NONROAD model (EPA 2006b). This model estimates fuel consumption based on estimated equipment/vehicle use (in hours) and average fuel consumed per hour of use. Since the fuel estimates are not based upon documented fuel sales or consumption, a fair degree of uncertainty accompanies these estimates.

Estimates of distillate fuel sales for ships and boats were obtained from EIA's Fuel Oil and Kerosene Sales (EIA 1991 through 2007). These estimates have a moderate level of uncertainty since EIA's estimates are based on survey data and reflect sales to economic sectors, which may include use by both mobile and non-mobile sources within a sector. Domestic consumption of residual fuel by ships and boats is obtained from EIA (2007b). These estimates fluctuate widely from year to year, and are believed to be highly uncertain. In addition, estimates of distillate and residual fuel sales for ships and boats are adjusted for bunker fuel consumption, which introduces an additional (and much higher) level of uncertainty.

Jet fuel and aviation gasoline consumption data are obtained from EIA (2007a) and FAA (2007). Estimates of jet fuel consumption are also adjusted downward to account for international bunker fuels, introducing a significant amount of uncertainty. Additionally, all jet fuel consumption in the transportation sector is assumed to be consumed by aircraft. Some fuel purchased by airlines is not used in aircraft but instead used to power auxiliary power units, ground equipment, and to test engines. Some jet fuel may also be used for other purposes such as blending with diesel fuel or heating oil.

In calculating CH_4 emissions from aircraft, an average emission factor is applied to total jet fuel consumption. This average emission factor takes into account the fact that CH_4 emissions occur only during the landing and take-off (LTO) cycles, with no CH_4 being emitted during the cruise cycle. However, a better approach would be to apply emission factors based on the number of LTO cycles.

Municipal Solid Waste Combustion

The upper and lower bounds of uncertainty in the CO_2 emissions estimate for Municipal Solid Waste Combustion are 13 percent and -20 percent respectively, and in the N_2O emission estimates are 184 percent and -66 percent respectively, relative to the respective 2006-Inventory estimates, at the 95% confidence interval. The uncertainties in the waste combustion emission estimates arise from both the assumptions applied to the data and from the quality of the data. Key factors include MSW combustion rate, fraction oxidized, missing data on MSW composition, average carbon content of MSW components, assumptions on the synthetic/biogenic carbon ratio, and combustion conditions affecting N_2O emissions. For more information on emission estimates from MSW combustion, please refer to the Municipal Solid Waste Combustion section of the Energy chapter. The highest levels of uncertainty surround the variables, whose estimates were developed based on assumptions (e.g., percent of clothing and footwear composed of synthetic rubber); the lowest levels of uncertainty surround variables that were determined by quantitative measurements (e.g., combustion efficiency, carbon content of carbon black). Important sources of uncertainty are as follows:

- *MSW Combustion Rate.* A source of uncertainty affecting both fossil CO_2 and N_2O emissions is the estimate of the MSW combustion rate. The EPA (2000a, 2003, 2005a, 2006; 2007; Schneider 2007) estimates of materials generated, discarded, and combusted carry considerable uncertainty associated with the material flows methodology used to generate them. Similarly, the *BioCycle* (Glenn 1999, Goldstein and Matdes 2000, Goldstein and Matdes 2001, Kaufman et al. 2004a, Kaufman et al. 2004b, Simmons et al. 2006) estimate of total waste combustion—used for the N_2O emissions estimate—is based on a survey of state officials, who use differing definitions of solid waste and who draw from a variety of sources of varying reliability and accuracy. The survey methodology changed significantly in 2003 and thus the results reported for 2002 are not directly comparable to the earlier results (Kaufman et al. 2004a, 2004b), introducing further uncertainty.

- *Fraction Oxidized.* Another source of uncertainty for the CO_2 emissions estimate is fraction oxidized. Municipal waste combustors vary considerably in their efficiency as a function of waste type, moisture content, combustion conditions, and other factors. A value of 98 percent was assumed for this analysis.

- *Missing Data on Municipal Solid Waste Composition.* Disposal rates have been interpolated when there is an incomplete interval within a time series. Where data are not available for years at the end of a time series, they are set equal to the most recent years for which estimates are available.

- *Average Carbon Contents.* Average carbon contents were applied to the mass of "Other" plastics combusted, synthetic rubber in tires and municipal solid waste, and synthetic fibers. These average values were estimated from the average carbon content of the known products recently produced. The actual carbon content of the combusted waste may differ from this estimate depending on differences in the chemical formulation between the known and unspecified materials, and differences between the composition of the material disposed and that produced. For rubber, this uncertainty is probably small since the major elastomers' carbon contents range from 77 to 91 percent; for plastics, it may be more significant, as their carbon contents range from 29 to 92 percent. However, overall, this is a small source of uncertainty.

- *Synthetic/Biogenic Assumptions.* A portion of the fiber and rubber in municipal solid waste is biogenic in origin. Assumptions have been made concerning the allocation between synthetic and biogenic materials based primarily on expert judgment.

- *Combustion Conditions Affecting N_2O Emissions.* Because insufficient data exist to provide detailed estimates of N_2O emissions for individual combustion facilities, the estimates presented exhibit high uncertainty. The emission factor for N_2O from municipal solid waste combustion facilities used in the analysis is an average of default values used to estimate N_2O emissions from facilities worldwide (Johnke 1999, UK: Environment Agency 1999, Yasuda 1993). These factors span an order of magnitude, reflecting considerable variability in the processes from site to site. Due to a lack of information on the control of N_2O emissions from MSW combustion facilities in the United States, the estimate of zero percent for N_2O emissions control removal efficiency also exhibits uncertainty.

Industrial Processes

The uncertainty analysis descriptions in this section correspond to some source categories included in the Industrial Processes Chapter of the Inventory.

Iron and Steel Production

The uncertainty upper and lower bounds of the CO_2 emission estimate for Iron and Steel Production were17 percent and -17 percent, respectively, at the 95 percent confidence interval. Factors such as the composition of C anodes and the C content of pig iron and crude steel affect CO_2 emissions from Iron and Still Production. For more information on emission estimates, please refer to the Iron and Steel Production section of the Industrial Processes chapter. Simplifying assumptions were made concerning the composition of C anodes, (80 percent petroleum coke and 20 percent coal tar). For example, within the aluminum industry, the coal tar pitch content of anodes can vary from 15 percent in prebaked anodes to 24 to 28 percent in Soderberg anode pastes (DOE 1997). An average value was assumed and applied to all carbon anodes utilized during aluminum and steel production. It was also assumed that the C contents of all pig iron and crude steel have carbon contents of 4 percent and 0.5 percent, respectively. The carbon content of pig iron can vary between 3 and 5 percent, while crude steel can have a carbon content of up to 2 percent, although it is typically less than 1 percent (IPCC 2000).

Ammonia Manufacture and Urea Consumption

The uncertainty upper and lower bounds of the emission estimate for Ammonia Manufacture and Urea Consumption were 12 percent and -10 percent, respectively, at the 95 percent confidence interval. The European Fertilizer Manufacturer's Association (EFMA) reported an emission factor range of 1.15 to 1.30 ton CO_2/ton NH_3, with 1.2 ton CO_2/ton NH_3 reported as a typical value. The actual emission factor depends upon the amount of air used in the ammonia production process, with 1.15 ton CO_2/ton NH_3 being the approximate stoichiometric minimum that is achievable for the conventional reforming process. By using natural gas consumption data for each ammonia plant, more accurate estimates of CO_2 emissions from ammonia production could be calculated. However, these consumption data are often considered confidential. Also, natural gas is consumed at ammonia plants both as a feedstock to the reforming process and for generating process heat and steam. Natural gas consumption data, if available, would need to be divided into feedstock use (non-energy) and process heat and steam (fuel) use, as CO_2 emissions from fuel use and non-energy use are calculated separately.[88]

Natural gas feedstock consumption data for the U.S. ammonia industry as a whole are available from the Energy Information Administration (EIA) *Manufacturers Energy Consumption Survey* (MECS) for the years 1985, 1988, 1991, 1994 and 1998 (EIA 1994, 1998). These feedstock consumption data collectively correspond to an effective average emission factor of 1.0 ton CO_2/ton NH_3, which appears to be below the stoichiometric minimum that is achievable for the conventional steam reforming process. The EIA data for natural gas consumption for the years 1994 and 1998 correspond more closely to the CO_2 emissions calculated using the EFMA emission factor than do data for previous years. The 1994 and 1998 data alone yield an effective emission factor of 1.1 ton CO_2/ton NH_3, corresponding to CO_2 emissions estimates that are approximately 1.5 Tg CO_2 Eq. below the estimates calculated using the EFMA emission factor of 1.2 ton CO_2/ton NH_3. Natural gas feedstock consumption data are not available from EIA for other years, and data for 1991 and previous years may underestimate feedstock natural gas consumption, and therefore the EFMA emission factor was used to estimate CO_2 emissions from ammonia production, rather than EIA data.

Research indicates that there is only one U.S. plant that manufactures ammonia from petroleum coke. CO_2 emissions from this plant are explicitly accounted for in the Inventory estimates. No data for ammonia plants using naphtha or other feedstocks other than natural gas have been identified. Therefore, all other CO_2 emissions from ammonia plants are calculated using the emission factor for natural gas feedstock. However, actual emissions may differ because processes other than catalytic steam reformation and feedstocks other than natural gas may have been used for ammonia production. Urea is also used for other purposes than as a nitrogenous fertilizer. Currently, urea used as a nitrogenous fertilizer is accounted for in the LULUCF chapter. Research has identified one ammonia production plant that is recovering byproduct CO_2 for use in EOR. Such CO_2 is currently assumed to remain sequestered (see the section of this chapter on CO_2 Consumption); however, time series data for the amount of CO_2 recovered from this plant are not available and therefore all of the CO_2 produced by this plant is assumed to be emitted to the atmosphere and allocated to Ammonia Manufacture.

Phosphoric Acid Production

The uncertainty upper and lower bounds of the emissions estimate for Phosphoric Acid Production were 19 percent and -18 percent, respectively, at the 95 percent confidence interval. Factors such as the composition of phosphate rock affect CO_2 emissions from phosphoric acid production. For more information on how emissions estimates were calculated, please refer to the Phosphoric Acid Production section of the Industrial Processes chapter. Only one set of data from the Florida Institute of Phosphate Research (FIPR) was available for the composition of phosphate rock mined domestically and imported, and data for uncalcined phosphate rock mined in North Carolina and Idaho were unavailable. Inorganic carbon content (as CO_2) of phosphate rock could vary ±1 percent, resulting in a variation in CO_2 emissions of ±20 percent.

Organic C is not included in the calculation of CO_2 emissions from phosphoric acid production. However, if, for example, 50 percent of the organic carbon content of the phosphate rock were to be emitted as CO_2 in the phosphoric acid production process, the CO_2 emission estimate would increase by on the order of 50 percent. If it is assumed that 100 percent of the reported domestic production of phosphate rock for Idaho and Utah was first calcined, and it is assumed that 50 percent of the organic carbon content of the total production for Idaho and Utah

[88] It appears that the IPCC emission factor for ammonia production of 1.5 ton CO_2 per ton ammonia may include both CO_2 emissions from the natural gas feedstock to the process and some CO_2 emissions from the natural gas used to generate process heat and steam for the process. Table 2-5, Ammonia Production Emission Factors, in Volume 3 of the *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories Reference Manual* (IPCC 1997) includes two emission factors, one reported for Norway and one reported for Canada. The footnotes to the table indicate that the factor for Norway does not include natural gas used as fuel but that it is unclear whether the factor for Canada includes natural gas used as fuel. However, the factors for Norway and Canada are nearly identical (1.5 and 1.6 tons CO_2 per ton ammonia, respectively) and it is likely that if one value does not include fuel use, the other value also does not. For the conventional steam reforming process, however, the EFMA reports an emission factor range for feedstock CO_2 of 1.15 to 1.30 ton per ton (with a typical value of 1.2 ton per ton) and an emission factor for fuel CO_2 of 0.5 tons per ton. This corresponds to a total CO_2 emission factor for the ammonia production process, including both feedstock CO_2 and process heat CO_2, of 1.7 ton per ton, which is closer to the emission factors reported in the *IPCC 1996 Reference Guidelines* than to the feedstock-only CO_2 emission factor of 1.2 ton CO_2 per ton ammonia reported by the EFMA. Because it appears that the emission factors cited in the *IPCC Guidelines* may actually include natural gas used as fuel, we use the 1.2 tons/ton emission factor developed by the EFMA.

was converted to CO_2 in the calcination process, the CO_2 emission estimate would increase on the order of 10 percent. If it were assumed that there are zero emissions from other uses of phosphate rock, CO_2 emissions would fall 10 percent.

Electric Transmission and Distribution

The uncertainty upper and lower bounds of the emissions estimate for Electric Transmission and Distribution at the 95 percent confidence interval were 17 percent and -16 percent, respectively. Uncertainty associated with emissions of SF_6 from electric transmission and distribution, stem from the following three quantities: (1) emissions from partners, (2) emissions from non-partners, and (3) emissions from manufacturers of electrical equipment. The uncertainty of partner emissions is related to whether the partner emissions are reported or estimated. For reported partner emissions, individual partner submitted SF_6 data was assumed to have an uncertainty of 10 percent. Based on a Monte Carlo analysis, the cumulative uncertainty of the total partner reported data was estimated to be 4.1 percent. For partner estimated emissions, the uncertainty associated with emissions extrapolated or interpolated from reported emissions data was assumed to be 20 percent. There are two sources of uncertainty which contribute to the non-partner emissions uncertainty, The first is the uncertainty in the coefficients of the regression equations used to estimate emissions from non-partners, and the second is the uncertainty in the total transmission miles for non-partners—the independent variable in the regression equation. The uncertainty in the coefficients (as defined by the regression standard error estimate) is estimated to be ±21 percent for small utilities and ±64 percent for large utilities, while the uncertainty in the transmission miles is assumed to be 10 percent. For equipment manufacturers, the quantity of SF_6 charged into equipment by equipment manufacturers is estimated using partner reported new nameplate capacity data and the estimate for the total industry nameplate capacity. The quantity of SF_6 charged into equipment in 2006 is estimated to have an uncertainty of 49 percent, and is derived from the uncertainty in partner reported new nameplate capacity (estimated as 5 percent using error propagation) and the uncertainty in the estimate for U.S. total nameplate capacity (assumed to be 70 percent).

A Monte Carlo analysis was applied to estimate the overall uncertainty of the 2006 emission estimate for SF_6 from electrical transmission and distribution. For each defined parameter (i.e., regression coefficient, transmission mileage, and partner-reported and partner-estimated SF_6 emissions data for electric power systems; and SF_6 emission rate and statistics for manufacturers), random variables were selected from probability density functions, all assumed to have normal distributions about the mean

Aluminum Production

The uncertainty upper and lower bounds of the PFCs emissions estimate for Aluminum Production were 8 percent and -8 percent, respectively, at the 95 percent confidence interval. The uncertainties associated with three variables were estimated for each smelter: (1) the quantity of aluminum produced, (2) the anode effect minutes per cell day (which may be reported directly or calculated as the product of anode effect frequency and anode effect duration), and (3) the smelter- or technology-specific slope coefficient. For more information on the effect of these variables on PFC emissions, please refer the Aluminum Production section of the Industrial Processes chapter. All three types of data are assumed to be characterized by a normal distribution. The uncertainty in aluminum production estimates was assumed to be 2 percent for reported data (IPCC 2006). For reported anode effect frequency and duration data, the uncertainties were assumed to be 2 percent and 5 percent, respectively (Kantamaneni et al. 2001). For the three smelters that participated in the 2003 EPA-funded measurement study, the uncertainties in the smelter-specific CF_4 and C_2F_6 slope coefficients were calculated to be 10 percent. For the two smelters with smelter-specific slope coefficients based on older studies, the uncertainty in the coefficients was assumed to be similar to that given by the IPCC guidance for technology-specific (Tier 2) slope coefficients. For the remaining 10 operating smelters, for which weighted average slope-factors were calculated based on technology-specific IPCC (2001) values, the uncertainty in the weighted average slope coefficients was based on information provided in IPCC (2001) for CWPB smelters, the technology type that makes up most of the production capacity of the 10 smelters. Consequently, the uncertainties assigned to the slope coefficients for CF_4 and C_2F_6 were 10 percent and 22 percent, respectively. (The uncertainty in CF_4 emissions is reported as 6 percent in IPCC (2001), but was increased to 10 percent in this analysis to better account for measurement uncertainty.) In general, where precise quantitative information was not available on the uncertainty of a parameter, an upper-bound value was used.

Magnesium Production

The uncertainty information below pertains to the emission estimates presented in the Magnesium Production section of the Industrial Processes chapter. Please refer to that section for more information about this source. The uncertainty upper and lower bounds of the emissions estimate for Magnesium Production were 14 percent and -14 percent, respectively, at the 95 percent confidence interval. An uncertainty of 5 percent was assigned to the data reported by each participant in the Partnership. If Partners did not report emissions data during the current reporting year, SF_6 emissions data were estimated using available emission factor and production information reported in prior years; the extrapolation was based on the average trend for Partners reporting in the current reporting year and the year prior. The uncertainty associated with the SF_6 usage estimate generated from the extrapolated emission factor and production information was estimated to be 30 percent. For those industry processes that are not represented in Partnership, such as permanent mold and wrought casting, SF_6 emissions were estimated using production and consumption statistics reported by USGS and estimated process-specific emission factors. The uncertainties associated with the emission factors and USGS-reported statistics were assumed to be 75 percent and 25 percent, respectively. Emissions associated with sand casting activities not entirely captured by the Partnership utilized a Partner-reported emission factor with an uncertainty of 50 percent. Estimated emissions for a secondary production facility participating in the Partnership were assigned an uncertainty of 75 percent due to an absence of reporting data.

Agriculture

The uncertainty analysis descriptions in this section correspond to some source categories included in the Agriculture Chapter of the Inventory.

Agriculture Manure Management

The uncertainty information below pertains to the emission estimates presented in the Agriculture Manure Management section of the Agriculture chapter. Please refer to that section for information about various manure management systems and their affect on emissions from this source. The uncertainty upper and lower bounds of the CH_4 emissions estimate for Manure Management were 20 percent and -18 percent, respectively, at the 95 percent confidence interval. The primary factors that contribute to the uncertainty in emission estimates are a lack of information on the usage of various manure management systems in each regional location and the exact CH_4 generating characteristics of each type of manure management system. Because of significant shifts in the swine and dairy sectors toward larger farms, it is believed that increasing amounts of manure are being managed in liquid manure management systems. The existing estimates reflect these shifts in the weighted MCFs based on the 1992, 1997, and 2002 farm-size data. However, the assumption of a direct relationship between farm size and liquid system usage may not apply in all cases and may vary based on geographic location. In addition, the CH_4 generating characteristics of each manure management system type are based on relatively few laboratory and field measurements, and may not match the diversity of conditions under which manure is managed nationally.

Previously, IPCC published a default range of MCFs for anaerobic lagoon systems of 0 to 100 percent, reflecting the wide range in performance that may be achieved with these systems (IPCC 2000). There exist relatively few data points on which to determine country-specific MCFs for these systems. In the United States, many livestock waste treatment systems classified as anaerobic lagoons are actually holding ponds that are substantially organically overloaded and therefore not producing CH_4 at the same rate as a properly designed lagoon. In addition, these systems may not be well operated, contributing to higher loading rates when sludge is allowed to enter the treatment portion of the lagoon or the lagoon volume is pumped too low to allow treatment to occur. Rather than setting the MCF for all anaerobic lagoon systems in the United States based on data available from optimized lagoon systems, a MCF methodology utilizing the van't Hoff-Arrhenius equation was developed to more closely match observed system performance and account for the affect of temperature on system performance.

The MCF methodology used in the inventory includes a factor to account for management and design practices that result in the loss of VS from the management system. This factor is currently estimated based on data from anaerobic lagoons in temperate climates, and from only three systems. However, this methodology is intended to account for systems across a range of management practices.

Uncertainty also exists with the maximum CH_4 producing potential of VS excreted by different animal groups (i.e., B_o). The B_o values used in the CH_4 calculations are published values for U.S. animal waste. However, there are several studies that provide a range of B_o values for certain animals, including dairy and swine. The B_o

values chosen for dairy assign separate values for dairy cows and dairy heifers to better represent the feeding regimens of these animal groups. For example, dairy heifers do not receive an abundance of high energy feed and consequently, dairy heifer manure will not produce as much CH_4 as manure from a milking cow. However, the data available for B_o values are sparse, and do not necessarily reflect the rapid changes that have occurred in this industry with respect to feed regimens.

Rice Cultivation

The uncertainty upper and lower bounds of the emissions estimate for Rice Cultivation were 119 percent and -65 percent, respectively, at the 95 percent confidence interval. Factors such as primary rice-cropped area, rationing, and flooding affect greenhouse gas emissions from this source. For more information on emissions estimates for Rice Cultivation, please refer to that section in the Agriculture Chapter. Uncertainty associated with primary rice-cropped area for each state was assumed to range from 1 percent to 5 percent of the mean area based on expert judgment. A normal distribution of uncertainty, truncated to avoid negative values, was assumed about the mean for areas.

Ratooned area data are an additional source of uncertainty. Although ratooning accounts for only 5 to 10 percent of the total rice-cropped area, it is responsible for about 15 to 30 percent of total emissions. For states that have never reported any ratooning, it is assumed with complete certainty that no ratooning occurred in 2006. For states that regularly report ratooning, uncertainty is estimated to be between 3 percent and 5 percent (based on expert judgment) and is assumed to have a normal distribution, truncated to avoid negative values. For Arkansas, which reported ratooning in 1998 and 1999 only, a triangular distribution was assumed, with a lower boundary of 0 percent ratooning and an upper boundary of 0.034 percent ratooning based on the maximum ratooned area reported in 1998 and 1999.

The practice of flooding outside of the normal rice season is also an uncertainty. According to agricultural extension agents, all of the rice-growing states practice this on some part of their rice acreage. Estimates of these areas range from 5 to 68 percent of the rice acreage. Fields are flooded for a variety of reasons: to provide habitat for waterfowl, to provide ponds for crawfish production, and to aid in rice straw decomposition. To date, however, CH_4 flux measurements have not been undertaken over a sufficient geographic range or under a broad enough range of representative conditions to account for this source in the emission estimates or its associated uncertainty.

Agricultural Soil Management

The uncertainty information below pertains to the emission estimates presented in the Agriculture Soil Management section of the Agriculture chapter. Please refer to that section for information about this source. For direct emissions calculated using DAYCENT, uncertainty in the results was attributed to model inputs (i.e., activity data, weather and soil conditions) and the structure of the model (i.e., underlying model equations and parameterization). A Monte Carlo analysis was implemented to address these uncertainties and propagate errors through the modeling process (Del Grosso et al., in prep). The analysis was conducted using probability distribution functions (PDFs) for weather, soil characteristics, and N inputs to simulate direct N_2O emissions for each crop- or grassland type in a county. A joint PDF was used to address the structural uncertainty for direct N_2O emissions from crops, which was derived using an empirically-based method (Ogle et al. 2007). This same Monte Carlo analysis was used to derive uncertainty for the volatilization, runoff, and leaching of N that had been estimated with DAYCENT. County-scale PDFs for weather were based on the variation in temperature and precipitation as represented in DAYMET weather data grid cells (1x1 km) occurring in croplands and grasslands in a county. The National Land Cover Dataset (Vogelman et al. 2001) provided the data on distribution of croplands and grasslands. Similarly, county-scale PDFs for soil characteristics were based on STATSGO Soil Map Units (Soil Survey Staff 2005), that occurred in croplands and grasslands. PDFs for fertilizer were derived from survey data for major U.S. crops, both irrigated and rainfed (ERS 1997; NASS 2004, 1999, 1992; Grant and Krenz 1985). State-level PDFs were developed for each crop if a minimum of 15 data points existed for each of the two categories (irrigated and rainfed). Where data were insufficient at the state-level, PDFs were developed for multi-state Farm Production Regions. Uncertainty in manure application for specific crops was incorporated into the analysis based on total manure available for application in each county, a weighted average application rate, and the crop-specific land area amended with manure for 1997 (compiled from USDA data on animal numbers, manure production, storage practices, application rates and associated land areas receiving manure amendments; see Edmonds et al. 2003). Together with the total area for each crop within a county, the result yielded a probability that a given crop in a specific county would either receive manure or not in the Monte Carlo analysis. A ratio of manure N available for application in each year of the inventory relative to 1997 was used to adjust the amount of area amended with manure, under the assumption that changing the amount of manure N available for application would lead to a proportional change in amended area (see the section on Major Crop Types on Mineral Soils for data sources on manure N availability). If soils were amended with manure, a reduction factor was applied to the N fertilization rate accounting for the interaction between fertilization and manure N amendments (i.e., producers reduce mineral fertilization rates if applying manure). Reduction factors were randomly selected from probability distribution factors based on relationships between manure N application and fertilizer rates from USDA cropping survey data (ERS 1997).

An empirically-based uncertainty estimator was developed using a method described by Ogle et al. (2007) to assess uncertainty in model structure associated with the algorithms and parameterization. The estimator was based on a linear mixed-effect modeling analysis comparing N_2O emission estimates from eight agricultural experiments with 50 treatments. Although the dataset was relatively small, modeled emissions were significantly related to measurements with a p-value of less than 0.01. Random effects were included to capture the dependence in time series and data collected from the same experimental site, which were needed to estimate appropriate standard deviations for parameter coefficients. The structural uncertainty estimator accounted for bias and prediction error in the DAYCENT model results, as well as random error associated with fine-scale emission predictions in counties over a time series from 1990 to 2006. Note that the current application only addresses structural uncertainty in cropland estimates; further development will be needed to address this uncertainty in model estimates for grasslands, which is a planned improvement as more soil N_2O measurement data become available for grassland sites. In general, DAYCENT tended to underestimate emissions if the rates were above 6 g N_2O m^{-2} (Del Grosso et al., in prep). Model structural uncertainty was not assessed for N volatilization and leaching/runoff, because sufficient data from field experiments were not available.

A simple error propagation method (IPCC 2006) was used to estimate uncertainties for direct emissions estimated with Tier 1 methods, including management of non-major crops (mineral fertilization, crop residues, organic fertilizers) and N inputs that were not addressed in the DAYCENT simulations (i.e., sewage sludge N, PRP manure N excreted on federal grasslands). Similarly, indirect emissions from N inputs that were not simulated with DAYCENT were calculated according to the IPCC methodology using the simple error propagation method (IPCC 2006). PDFs for the proportion of N subject to volatilization, leaching and runoff, as well as indirect N_2O emission factors were based on IPCC (2006), and PDFs for the activity data were based on the uncertainties associated underlying survey information and calculations.[89] For lands simulated by DAYCENT, uncertainty in indirect emissions was derived using the simple error propagation approach, combining uncertainty from the DAYCENT outputs for N volatilization and leaching/runoff with uncertainty in the indirect N_2O emission factors (IPCC 2006).

Field Burning of Agricultural Residues

The uncertainty upper and lower bounds of the CH_4 emissions estimate for Field Burning of Agricultural Residues were 78 percent and -65 percent, respectively, and of the N_2O emissions estimate were 72 percent and -64 percent respectively, at the 95 percent confidence interval. Variables such as crop production, residue/crop product ratios, and burning and combustion efficiencies affect greenhouse gas emission estimates for Field Burning of Agricultural Residues. For more information on emission estimates, please refer to the Field Burning of Agricultural Residues section of the Agriculture Chapter. The uncertainty in production for all crops considered here is estimated to be 5 percent, based on expert judgment. Residue/crop product ratios can vary among cultivars. Generic residue/crop product ratios, rather than ratios specific to the United States, have been used for all crops except sugarcane. An uncertainty of 10 percent was applied to the residue/crop product ratios for all crops. Based on the range given for measurements of soybean dry matter fraction (Strehler and Stützle 1987), residue dry matter contents were assigned an uncertainty of 3.1 percent for all crop types. Burning and combustion efficiencies were assigned an uncertainty of 5 percent based on expert judgment.

The N_2O emission ratio was estimated to have an uncertainty of 28.6 percent based on the range reported in IPCC/UNEP/OECD/IEA (1997). The uncertainty estimated for the CH_4 emission ratio was 40 percent based on the range of ratios reported in IPCC/UNEP/OECD/IEA (1997).

[89] With the exception of organic fertilizers and crop yields, which were assumed to have a default ±50 percent uncertainty.

Land Use, Land-Use Change, and Forestry

The uncertainty analysis descriptions in this section correspond to some source categories included in the Land Use, Land-Use Change and Forestry Chapter of the Inventory.

Forest Land Remaining Forest Land

Changes in Forest Carbon Stocks

Forest area data from the USDA Forest Service and C density data affect total net flux of forest C estimates. For more information on net forest C flux, please refer to the Changes in Forest Carbon Stocks section of the Land Use, Land-Use Change, and Forestry (LULUCF) chapter. The USDA Forest Service inventories are designed to be accurate within 3 percent at the 67 percent confidence level (one standard error) per 405,000 ha (1 million acres) of timberland (USDA Forest Service 2006c). For larger areas, the uncertainty in area is concomitantly smaller, and precision at plot levels is larger. An analysis of uncertainty in growing stock volume data for timber producing land in the Southeast by Phillips et al. (2000) found that nearly all of the uncertainty in their analysis was due to sampling rather than the regression equations used to estimate volume from tree height and diameter. The quantitative uncertainty analysis summarized here primarily focuses on uncertainties associated with the estimates of specific C stocks at the plot level and does not address error in tree diameters or volumes.

Estimates for stand-level C pools are derived from extrapolations of site-specific studies to all forest land, because survey data on these pools are not generally available. Such extrapolation introduces uncertainty because available studies may not adequately represent regional or national averages. Uncertainty may also arise due to: (1) modeling errors (e.g., relying on coefficients or relationships that are not well known); and (2) errors in converting estimates from one reporting unit to another (Birdsey and Heath 1995). An important source of uncertainty is that there is little consensus from available data sets on the effect of land-use change and forest management activities (such as harvest) on soil C stocks. For example, while Johnson and Curtis (2001) found little or no net change in soil C following harvest, on average, across a number of studies, many of the individual studies did exhibit differences. Heath and Smith (2000) noted that the experimental design in a number of soil studies limited their usefulness for determining effects of harvesting on soil C. Because soil C stocks are large, estimates need to be very precise, since even small relative changes in soil C sum to large differences when integrated over large areas. The soil C stock and stock change estimates presented here are based on the assumption that soil C density for each broad forest type group stays constant over time. The state of information and modeling are improving in this regard (Woodbury et al. 2006, 2007); the effects of land use and of changes in land use and forest management will be better accounted for in future estimates of soil C.

Uncertainty in estimates about the HWP Contribution is based on Monte Carlo simulation of the production approach. The uncertainty analysis is based on Skog et al. (2004), with later revisions made in conjunction with overall revisions in the HWP model (Skog in preparation). The uncertainty analysis for HWP includes an evaluation of the effect of uncertainty in 13 sources including production and trade data, factors to convert products to quantities of C, rates at which wood and paper are discarded, and rates and limits for decay of wood and paper in SWDS.

Non-CO_2 Emissions from Forest Fires

The uncertainty information below pertains to the emission estimates presented in the Non-CO_2 Emissions from Forest Fires section of the LULUCF chapter. Please refer to that section for information about forest area estimates, average C density, and combustion factors, and emission estimates from this source. The uncertainty upper and lower bounds of the CH_4 emissions estimate from Forest Fires were 92 percent and -71 percent, respectively, and of the N_2O emissions estimate 93 percent and -70 percent, respectively, at the 95 percent confidence interval. To quantify the uncertainties for emissions from forest fires, a Monte Carlo (Tier 2) uncertainty analysis was performed using the information provided above. The uncertainty inputs are described in more detail in the section on non-CO_2 emissions from forest fires.

Uncertainty in forest area was estimated to be ±0.24 percent for the 95 percent confidence interval (Heath 2006a). This estimate was calculated based on FIA accuracy standards, which mandate that sampling error cannot exceed 3 percent error per 1 million acres of timberland (Heath 2006a). Uncertainty in average C density was estimated to be ±0.4 percent for the lower 48 States and ±1.2 percent for Alaska (Heath 2006a, 2006b). Uncertainty in the area of forest land considered to be under protection from fire and the total area considered to be under protection from fire were assumed to be 30 percent (IPCC 2003). Uncertainties in emission ratios were based on IPCC (2003) guidance to apply a 70 percent uncertainty range. Since the combustion factor (0.4) was a default IPCC (2003) value, the uncertainty range provided by IPCC (0.36 to 0.45) was assumed.

Direct N_2O fluxes from Forest Soils

The uncertainty upper and lower bounds of the emissions estimate for Direct N_2O Fluxes from Forest Soils were 211 percent and -59 percent, respectively, at the 95 percent confidence interval. Variables such as the emission factor for synthetic fertilizer applied to soil, and the area of forest land receiving fertilizer affect direct N_2O fluxes from Forest Soils. For more information, please refer to that section of the LULUCF chapter. The uncertainty range of the IPCC default emission factor for synthetic fertilizer applied to soil, according to IPCC (2006), ranges from 0.3 to 3 percent. Because IPCC does not provide further information on whether this range represents the 95 percent confidence interval or the absolute minimum and maximum values, a triangular distribution was used to represent the uncertainty of the emission factor. The uncertainty in the area of forest land receiving fertilizer was conservatively estimated at ±20 percent and in fertilization rates at ±50 percent (Binkley 2004).

Cropland Remaining Cropland

The uncertainty information below pertains to the emission estimates presented in the Cropland Remaining Cropland section of the LULUCF chapter. Please refer to that section for information about this source. The uncertainty upper and lower bounds of the emissions estimate for Cropland Remaining Cropland were 35 percent and -38 percent, respectively, at the 95 percent confidence interval. Probability Distribution Functions (PDFs) for fertilizer were based on survey data for major U.S. crops, both irrigated and rainfed (ERS 1997; NASS 2004, 1999, 1992; Grant and Krenz 1985). State-level PDFs were developed for each crop if a minimum of 15 data points existed for each of the two categories (irrigated and rainfed). Where data were insufficient at the state-level, PDFs were developed for multi-state Farm Production Regions. Uncertainty in manure applications for specific crops was incorporated in the analysis based on total manure available for use in each county, a weighted average application rate, and the crop-specific land area amended with manure (compiled from USDA data on animal numbers, manure production, storage practices, application rates and associated land areas receiving manure amendments; see Edmonds et al. 2003). Together with the total area for each crop within a county, this yielded a probability that a given crop at a specific NRI point would either receive manure or not. A ratio of managed manure N production in each year of the inventory relative to 1997 was used to adjust the probability of an area receiving an amendment, under the assumption that greater or less managed manure N production would lead to a proportional change in amended area (see Tier 3 Methods Section for data sources on manure N production). Manure amendment areas were averaged across decades to produce the PDF for the Monte Carlo Analysis (i.e., 1980-1989, 1990-2000). If soils were amended with manure, a reduction factor was applied to the N fertilization rate accounting for the interaction between fertilization and manure N amendments (i.e., producers often reduce mineral fertilization rates if applying manure). Reduction factors were randomly selected from probability distribution factors based on relationships between manure N application and fertilizer rates (ERS 1997). For tillage uncertainty, transition matrices were constructed from CTIC data to represent tillage changes for two time periods, combining the first two and the second two management blocks (i.e., 1980-1989, 1990-2000). A Monte Carlo analysis was conducted with 100 iterations in which inputs values were randomly drawn from the PDFs to simulate the soil C stocks for each NRI cluster of points (i.e., inventory points in the same county were grouped into clusters if they had the same land-use/management history and soil type) using the Century model.

An empirically-based uncertainty estimator was developed to assess uncertainty in model structure associated with the algorithms and parameterization. The estimator was based on a linear mixed effect modeling analysis comparing modeled soil C stocks with field measurements from 45 long-term agricultural experiments with over 800 treatments, representing a variety of tillage, cropping, and fertilizer management practices (Ogle et al. 2006b). The final model included variables for organic matter amendments, N fertilizer rates, inclusion of hay/pasture in cropping rotations, use of no-till, setting-aside cropland from production and inclusion of bare fallow in the rotation. Each of these variables were found to be significant at a 95 percent probability level, and accounted for statistically significant biases in the modeled estimates from Century. For example, Century tended to under-estimate the influence of organic amendments on soil C storage, so a variable was added to adjust the estimate from Century. Random effects captured the dependence in time series and data collected from the same long-term experimental site, which were needed to estimate appropriate standard deviations for parameter coefficients. For each C stock estimate from the Monte Carlo analysis, the structural uncertainty estimator was applied to adjust the value accounting for bias and prediction error in the modeled values. The structural uncertainty estimator was applied by randomly drawing parameter coefficients from their joint probability distribution, in addition to random draws from PDFs representing the uncertainty due to site and site by year random effects. Finally, uncertainty in the land-use and management statistics from the NRI were incorporated into the analysis based on the sampling variance for the clusters of NRI points.

The NRI has a two-stage sampling design that allowed PDFs to be constructed assuming a multivariate normal distribution accounting for dependencies in activity data. PDFs for the tillage activity data, as provided by the CTIC, were constructed on a bivariate normal distribution with a log-ratio scale, accounting for the negative dependence among the proportions of land under conventional and conservation tillage practices. PDFs for the agricultural areas receiving manure were derived assuming a normal distribution from county-scale area amendment estimates derived from the USDA Census of Agriculture (Edmonds et al. 2003). Lastly, enrollment in wetland restoration programs was estimated from contract agreements, but due to a lack of information on the margin of error, PDFs were constructed assuming a nominal ±50 percent uncertainty range.

Uncertainties in Mineral Soil Carbon Stock Changes

Tier 3 Approach

The uncertainty information below pertains to the emission estimates presented in the Mineral Soil Carbon Stock Changes section of the LULUCF chapter. Please refer to that section for information about this source. The uncertainty analysis for the Tier 3 Century inventory had three components: 1) a Monte Carlo approach to address uncertainties in model inputs, 2) an empirically-based approach for quantifying uncertainty inherent in the structure of the Century model, and 3) scaling uncertainty associated with the NRI survey (i.e., scaling from the individual NRI points to the entire U.S. agricultural land base using the expansion factors).

For the model input uncertainty, probability distribution functions (PDFs) were developed for fertilizer rates, manure application and tillage practices. An empirically-based uncertainty estimator was developed to assess uncertainty in model structure associated with the algorithms and parameterization. The estimator was based on a linear mixed effect modeling analysis comparing modeled soil C stocks with field measurements from 45 long-term agricultural experiments with over 800 treatments, representing a variety of tillage, cropping, and fertilizer management practices (Ogle et al. 2007). The final model included variables for organic matter amendments, N fertilizer rates, inclusion of hay/pasture in cropping rotations, use of no-till, setting-aside cropland from production, and inclusion of bare fallow in the rotation. Each of these variables were found to be significant at a 0.05 alpha level, and accounted for statistically significant biases in modeled estimates from the Century model. Uncertainty in land-use and management statistics from the NRI were incorporated into the analysis based on the sampling variance for the clusters of NRI points.

Tier 2 Approach

For the Tier 2 IPCC method, a Monte Carlo approach was used (Ogle et al. 2003). PDFs for stock change factors were derived from a synthesis of 91 published studies, which addressed the impact of management on SOC storage. Uncertainties in land-use and management activity data were also derived from a statistical analysis.

Additional Mineral C Stock Change Calculations

A ±50 percent uncertainty was assumed for additional adjustments to the mineral soil C stocks between 1990 and 2006, accounting for additional C stock changes associated gains or losses in C sequestration after 1997 due to changes in Conservation Reserve Program enrollment.

Uncertainties in Organic Soil C Stock Changes

Uncertainty in C emissions from organic soils was estimated in the same manner described for mineral soil using the Tier 2 method and Monte Carlo analysis. PDFs for emission factors were derived from a synthesis of 10 studies, and combined with uncertainties in the NRI land use and management data for organic soils in the Monte

Carlo analysis. Please refer to the Organic Soil C Stock Changes section of the LULUCF chapter for more information on C emissions from organic soils.

Uncertainties in CO_2 Emissions from Liming

The uncertainty information below pertains to the emission estimates presented in the Mineral Soil Carbon Stock Changes section of the LULUCF chapter. Please refer to that section for information about liming activity data and the emission factors used for this source. A Monte Carlo (Tier 2) uncertainty analysis was applied to estimate the uncertainty of CO_2 emissions from liming. Uncertainties in the estimates of emissions from liming result from both the emission factors and the activity data. The emission factors used for limestone and dolomite take into account the fate of C following application to soils, including: dissolution of liming constituents; leaching of bicarbonates into the soil and transport to the ocean; and emissions to the atmosphere (West and McBride 2005). The C accounting behind these emission factors entails assumptions about several uncertain factors. First, it is uncertain what fraction of agricultural lime is dissolved by nitric acid (HNO_3)—a process that releases CO_2—and what portion reacts with carbonic acid (H_2CO_3), resulting in the uptake of CO_2. The fractions can vary depending on soil pH and nitrogen fertilizer use. The second major source of uncertainty is the fraction of bicarbonate (HCO_3^-) that leaches through the soil profile and *is transported into groundwater, which can eventually be transferred into rivers and into the ocean*. This fraction can vary depending on the soil pH and whether calcium (Ca^{2+}) and magnesium (Mg^{2+}) liming constituents that might otherwise accompany HCO_3^-, are taken up by crops, remain in the upper soil profile, or are transported through or out of the soil profile. Finally, the emission factors do not account for the time that is needed for leaching and transport processes to occur.

There are several sources of uncertainty in the limestone and dolomite activity data. When reporting data to the USGS (or U.S. Bureau of Mines), some producers do not distinguish between limestone and dolomite. In these cases, data are reported as limestone, so this reporting could lead to an overestimation of limestone and an underestimation of dolomite. In addition, the total quantity of crushed stone listed each year in the *Minerals Yearbook* excludes American Samoa, Guam, Puerto Rico, and the U.S. Virgin Islands. These areas are, thus, not included in the inventory estimates.

Land Converted to Cropland

Tier 2 Approach

The uncertainty upper and lower bounds of the emissions estimate for Land Converted to Cropland were 22 percent and -25 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Land Converted to Cropland* using the Tier 2 approach was based on the same method described for *Cropland Remaining Cropland*.

Uncertainties in Mineral and Organic Soil C Stock Changes

The quantitative estimates of uncertainty presented above are missing several components. This section qualitatively describes these contributors to overall uncertainty. The agricultural soil C inventory has undergone several improvements during the past few years, such as the development of the Tier 3 inventory method to estimate mineral soil C stock changes for the majority of U.S. cropland. However, some limitations remain in the analysis. First, the current agricultural soil C inventory includes some points designated as non-agricultural land-uses in the NRI if the points were categorized as cropland in either 1992 or 1997, but were urban, water, or miscellaneous non-cropland (e.g., roads and barren areas) in another year. The impact on soil organic C storage that results from converting non-agricultural uses to cropland is not well-understood, and therefore, those points were not included in the calculations for mineral soils (emissions from organic soils, however, were computed for those points in the years that they were designated as an agricultural use). Similarly, the effect of aquaculture (e.g., rice cultivation followed by crayfish production in flooded fields) on soil C stocks has not been estimated due to a lack of experimental data. Second, the current estimates may underestimate losses of C from organic soils because the *1997 National Resources Inventory* was not designed as a soil survey and organic soils frequently occur as relatively small inclusions within major soil types. Lastly, the IPCC Tier 2 methodology does not take into account changes in SOC stocks due to pre-1982 land use and land-use change.

Grassland Remaining Grassland

Tier 2 Approach

The uncertainty upper and lower bounds of the emissions estimate for Grassland Remaining Grassland were 15 percent and -18 percent, respectively, at the 95 percent confidence interval. The uncertainty analysis for *Grassland Remaining Grassland* using the Tier 2 approach was based on the same method described for *Cropland Remaining Cropland*. The uncertainty in the inventory estimate of a 0.2 Tg CO_2 Eq. removal was 89 percent below the mean and 127 percent above the mean.

Additional Uncertainties in Mineral and Organic Soil C Stock Changes

The quantitative estimates of uncertainty presented above are missing several components. This section qualitatively describes these contributors to overall uncertainty. Minimal data exist on where and how much sewage sludge has been applied to U.S. agricultural land and the accounting of this activity appears to be much more difficult than the related-activity of using manure to amend agricultural soils. Consequently, there is considerable uncertainty in the application of sewage sludge, which is assumed to be applied to *Grassland Remaining Grassland*. However, some sludge may be applied to other agricultural land, but there is not sufficient information to further subdivide application among the agricultural land use/land-use change categories. Another limitation is that the current estimates may underestimate losses of C from organic soils because the *1997 National Resources Inventory* was not designed as a soil survey and organic soils frequently occur as relatively small inclusions within major soil types. Lastly, the IPCC Tier 2 methodology does not take into account changes in SOC stocks due to pre-1982 land use and land-use change.

Land Converted to Grassland

Tier 2 Approach

The uncertainty upper and lower bounds of the emissions estimate for Land Converted to Grassland were 14 percent and -13 percent, respectively, at the 95 percent confidence interval, The uncertainty analysis for *Land Converted to Grassland* using the Tier 2 approach was based on the same method described for *Cropland Remaining Cropland*. See the Tier 2 section under minerals soils in the *Cropland Remaining Cropland* section for additional discussion.

Additional Uncertainties in Mineral and Organic Soil Carbon Stock Changes

The quantitative estimates of uncertainty presented above are missing several components. This section qualitatively describes these contributors to overall uncertainty. The agricultural soil C inventory has undergone several improvements during the past few years, such as the development of the Tier 3 inventory method to estimate mineral soil C stock changes for the majority of U.S. grassland. However, some limitations remain in the analysis. First, the current agricultural soil C inventory includes some points designated as non-agricultural land-uses in the NRI if the points were categorized as agricultural land use in either 1992 or 1997, but were urban, water, or miscellaneous non-cropland (e.g., roads and barren areas) in another year. The impact on SOC storage that results from converting non-agricultural uses to grassland is not well-understood, and therefore, those points were not included in the calculations for mineral soils (emissions from organic soils, however, were computed for those points in the years that they were designated as grassland). Second, the current estimates may underestimate losses of C from organic soils because the *1997 National Resources Inventory* was not designed as a soil survey and organic soils frequently occur as relatively small inclusions within major soil types. Lastly, this IPCC Tier 2 methodology does not take into account changes in SOC stocks due to pre-1982 land use and land-use change.

Settlements Remaining Settlements

N_2O Fluxes from Settlement Soil

The uncertainty information below pertains to the emission estimates presented in the N_2O Fluxes from Settlement Soil section of the LULUCF chapter. Please refer to that section for information about synthetic fertilizer N, the amounts of sewage sludge applied to non-agricultural lands, and other variables that affect this source. The uncertainty upper and lower bounds of the emissions estimate for N_2O fluxes from Settlement Soil were 280 percent and -79 percent, respectively, at the 95 percent confidence interval. The uncertainty range for the IPCC's default emission factor for mineral and organic N additions applied to soil ranges from 0.3 to 3 percent (IPCC 2006). Because the IPCC does not provide further information on whether this range represents the 95 percent confidence interval or the absolute minimum and maximum values, a triangular distribution was used to represent the uncertainty of the emission factor.

The uncertainty in the total amount of synthetic fertilizer N applied in the United States was estimated to be ±3 percent (Terry 2005). The uncertainty in the amount of synthetic fertilizer N applied to settlement soils was conservatively estimated to be ±50 percent, since no uncertainty was provided in Ruddy et al. (2006). The uncertainty in the amounts of sewage sludge applied to non-agricultural lands and used in surface disposal was based on the uncertainty of the following data points, which were used to determine the amounts applied in 2005: (1) N content of sewage sludge; (2) total sludge applied in 2000; (3) wastewater existing flow in 1996 and 2000; and (4) the sewage sludge disposal practice distributions to non-agricultural land application and surface disposal**.**

(1) The value assumed for N content of sewage sludge could range from around 0.1 percent to around 17 percent (McFarland 2001). Because information was not available on the distribution, a triangular distribution was assumed based on IPCC guidelines.
(2) The uncertainty in the total amount of sludge applied in 2000 was based on a comparison with similar data available from other publications, which were all within 3 percent of the value used in the Inventory calculations (BioCycle 2000, NRC 2002, WEF 1997, Bastian 1997). The distribution was estimated to be normal based on expert opinion (Boucher 2006).
(3) The uncertainty in the wastewater existing flow values for 1996 and 2000 was estimated at 0.0625 percent with a lognormal distribution (Plastino 2006).
(4) The uncertainty in the sewage sludge disposal practice distributions was based on a comparison with similar data available from other publications, which were at most 12 percent different than the distribution for non-agricultural land application used in the Inventory calculations and at most 69 percent different than the distribution for surface disposal used in the Inventory calculations (Biocycle 2000, NRC 2002).

Other

The uncertainty analysis descriptions in this section correspond to Changes in Yard Trimming and Food Scrap Carbon Stocks in Landfills source category included in the Other Chapter of the Inventory.

Changes in Yard Trimming and Food Scrap Carbon Stocks in Landfills

The uncertainty upper and lower bounds of the emissions estimate for Yard Trimming and Food Scrap Stocks in Landfills were 94 percent and -41 percent, respectively, at the 95 percent confidence interval. Please refer to the Yard Trimming and Food Scrap Carbon Stocks in Landfills section of the LULUCF chapter for more information on the emissions estimate for this source. The uncertainty ranges were assigned based on expert judgment and are assumed to be normally distributed around the inventory estimate, except for the values for decomposition rate, proportion of C stored, and moisture content for branches. The uncertainty ranges associated with these values are highlighted separately in this section.

The uncertainty range selected for input variables for the proportions of both grass and leaves in yard trimmings was 20 to 60 percent. The initial C content for grass, leaves, and food scraps (all expressed as percentages in the calculations for the inventory) were plus or minus 10 percent. For the moisture content of branches (where the inventory estimate is 10 percent), the uncertainty range was assumed to be 5 to 30 percent, within a lognormal distribution.

The uncertainty ranges associated with the disposal of grass, leaves, branches, and food scraps were bound at 50 percent to 150 percent of the inventory estimates. The half-life of grass was assumed to range from 1 to 15 years, the half-life of food scraps was assumed to range from 1 to 20 years, the half-life of leaves was assumed to range from 2 to 30 years, and the half life of branches was assumed to range from 5 to 50 years. Finally, the proportion of C stored in grass, leaves, branches, and food scraps was assumed to vary plus or minus 20 percent from the best estimate, with a uniform distribution.

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